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Supervised Machine Learning Methods for Early Detection of Untrue Information

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Abstract

The spread of untrue information has become a serious issue in the current social media world. It is the propagation of dishonest intentions to mislead people. Though, there are many forms of untrue information types. For users to find information or news in real-time, Twitter is one of the major social media web pages. This paper uses the Higgs boson dataset, which presents the anatomy of the spread of scientific rumors through the follow-up and analysis of the related Twitter user behavior before and after its announcement. Models describe the early detection of untrue information with the desired accuracy. The paper analyses the behavior patterns of people who tweeted over the timeframe with Machine Learning (ML) algorithms about this discovery. The highest achievable accuracy of untrue information with logistic regression (LR) and random forest (RF) was 93% for 1 day in the retweet network.

Disciplinary: Computer Science & Engineering, Information Technology.

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1 Introduction

Twitter is one of the most widely used sites to share news around the globe. Extravagantly sharing and exchanging data came to visit with the limitation of misleading readers with a huge amount of recent knowledge every second. Unfortunately, not every piece of information is reliable. There are several descriptions of rumors used in literature. However, one of the most adopted meanings (Yang et al., 2016) is that rumor is described as "a story of a statement whose true value is unverified" (Qazvinian et al., 2011). The consistency with these rumors shows they may not have to be false but were later considered real or false. The most characteristic of the rumors is that the true value is not verified at the time of posting. Existing exploration in rumor propagation and identification inspects the conduct of misinformation posts over the organization-based dissemination speed, profundity, focus, area, and now and then consolidating highlights to separate posts. In any case, with access limitations to the whole Twitter network diagram and posts, looks at how individual clients add to the dissemination in rumors posts with highlights of the post sharer and recipients impact this worldview.

2 Related Works

The spread, detection, and control of true and untrue/false information online continue to be a topic of interest to researchers in humanities, social sciences, and engineering.

2.1 Information Diffusion

The measurement of information diffusion was observed via the diffusion graph and the rates at which the nodes in the graph were chosen. The diffusion graph shows the effect of viral marketing on the network (And *et al.*, 2003; Chen and Wang, 2010; Domingos, 2005), emergency communication (Muraki., 2011), and retweet ability (Nguyen *et al.*, 2012). The influential research models focus on relationship strength based on the proximity and contact activities of the profile (Xiang *et al.*, 2010; Nguyen *et al.*, 2012). Distinguishing compelling clients discovered to be valuable when attempting to choose seed nodes locally that will boost the spread of information across the networks (Pei *et al.*, 2014). Worked on finding the best spreaders in unique social stages when the total worldwide network structure is inaccessible. Wu *et al.* (2014) observed that (a) the authority of a persuasive client via online media which can be utilized to change the assessments of the clients and (b) assessment similitude factors where clients will in general acknowledge on the assessment that is like his own.

2.2 Rumor Detection

"Rumors normally refer to information which is deliberately false or whose truth value is unverifiable at the time of circulation (DiFonzo, 2007)". The problem with rumor identity is usually a binary or higher multiple rating problem (Castillo *et al.*, 2011; Chen *et al.*, 2018). For the classification mission, such models take into account one or more features of the data. It's critical to spot rumors early on in their spread so that appropriate steps can be taken to minimize network harm (Ma *et al.*, 2018). It will become increasingly difficult to monitor rumors as they spread to a wider audience. As a result, identifying rumors at an early stage with high precision would aid in faster rumor control than discovering rumors at a later stage.

There are fewer testing projects for gossip identification in earlier stages. Early approaches to identification of rumors, including DSTS (Ma *et al.*, 2015), CERT (Wu, 2017), conversation-based methodology (Sampson *et al.*, 2016), and by using machine-based teaching approaches manually.

3 Design Methodology

This system uses Higgs Boson Dataset (De Domenico *et al.*, 2013) to investigate the distribution of Twitter data knowledge processes both before, during, and after new particle announcement. A scientific rumor propagation through their interactions such as to reply, retweet, and mention of tweets. In Figure 1, data is preprocessed to find rumors labeled 1 and 0. Labeling performed to distinguish the tweets among the users that are fall in the rumor category. The interaction between tweets represents untrue/rumor to be 1 and non-rumor/true as 0. The dataset was split into x variables as inputs labeled with User A, User B, and Timestamp, and Y holds the interactions to be Mention, Retweet, and Reply. To review information dissemination processes on Twitter data before, during, and after the announcement of a new particle. Besides, each data is processed in 4-time frames, i.e. scientific rumor spread over 1 day, 3 days, 5 days, and 7 days. K-Nearest Neighbor (KNN), Logistic Regression (LR), Decision Tree (DT), and Random Forest (RF) techniques are used for data training. Thus, analyzed in making predictions and scoring their accuracy.

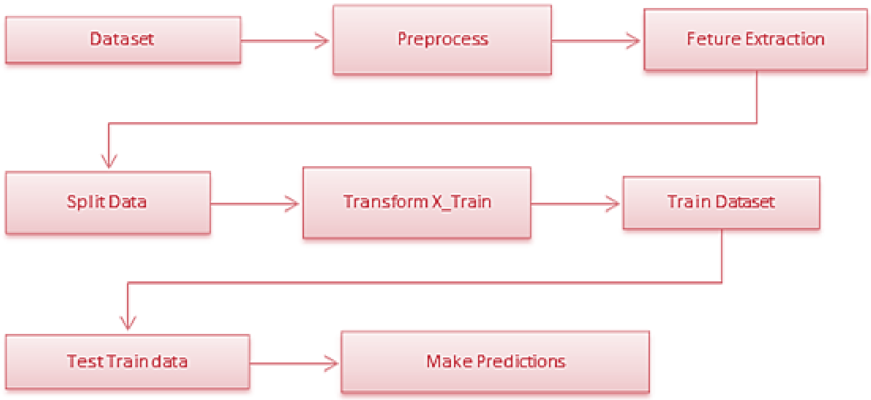

Figure 1: Flowchart for Research Methodology and Design

3.1 Proposed Work

Dynamic SEIZ, a proposed enhanced disease model (Mathur *et al.*, 2020) categorizes the population (N) in four different categories (i.e. "Susceptible (S), Exposed (E), Infected (I), Skeptic(Z)"). The chances of change from one state to another are used to characterize misinformation from actual data. Comparisons and analysis of data between traditional and dynamic network SEIZ provide an early indication and discern the population change rate with time on Twitter. The limitation was neglecting the classes that identify untrue information rather gives time series prediction of 1 day as the spread of false data. With this identification of content being untrue was found in just 1 day but unable to find activities from different classes (i.e., Mention Tweet (MT), Reply Tweet (RE), Retweet (RT)).

To solve this issue, we have derived a Machine learning method to early predict untrue information between activity classes of Twitter. In our proposed method, Machine Learning Algorithms classifies data into three classes MT, RE, RT for finding untrue information as early as possible using multi-class classifiers. These classifiers can predict untrue information by evaluating certain metrics to identify and predict it early as soon as possible for 7 days data.

4 Experimental Evaluation

4.1 Dataset

Higgs Boson Dataset has 14 million tweets data to discovery of new particle posed in Twitter between 1st and 7th July 2012 (De Domenico *et al.*, 2013). This represents the anatomy of spreading scientific rumors by analyzing user activities during and after the announcement of its release. All this information was publicly generated online by Stanford Network Analysis Project (SNAP). The availability of data set source for analyzing global dynamics of this scientific rumor around the world has 4 directive activities: -a) Re-tweeting (retweet network i.e., RT); b) Replying (reply network i.e., RT) to existing tweets; c) Mentioning (mention network i.e., MT); d) Friends/followers social relationships and activities about action on Twitter.

4.2 Supervised Classification Algorithms

4.2.1 Logistic Regression

Logistic regression (LR) is another procedure acquired by artificial intelligence (AI) from the area of insights. It is the go-to technique for paired classification (issues with two class values). Logistic regression resembles straightforward regression in that the objective is to search out the values for the coefficients that gauge each info variable. In contrast to straight regression, the prediction for the yield changed by utilizing a non-direct function called the logistic function. The logistic function appears to be a colossal S and can change any value into the reach 0 to 1. This is regularly helpful because we will apply a standard to the yield of the logistic function to snap values to 0 and 1 (for example on the off chance that yet 0.5, at that point yield 1) and predict a classification value.

4.2.2 K-Nearest Neighbors

The KNN algorithm uses the entire collection of information on the basis that the preparation defines, instead of dividing the information collected into a preparation set and test set. At a time when the result is necessary for an instance of substitution, the KNN algorithm experiences the whole knowledge index to see how closest the k-instances are to a new instance or how many instances like the new record are most realistic. At that point, the average value for a classification problem is (for a background problem) or mode (most continuous class). The user value is defined for value k. The similarity between instances calculated by the use of measures such as the Euclidean distance and the hamming distance.

4.2.3 Decision Tree Algorithms

One of the most accurate and unique machine learning algorithms is a decision tree (DT). It models decision logics, i.e., measures, and compares outcomes to characterize knowledge objects in a tree-like construction. The nodes of the DT tree usually have different levels where the most or most important node is called the root node. Each inner node (i.e., nodes with at least one child) performs tests on info factors or traits. Based on the test result, the classification calculation branches towards a worthy child node where the test and spreading technique before it reaches the leaf node. The leaf or terminal nodes compare the outcomes of the decisions.

4.2.4 Random Forest

It is an ensemble classifier and consists of a variety of DTs similar to the way a forest is made up of a variety of trees. DTs that become exceptionally deep regularly given the over-fitting of training information, resulting in a high range of classification results in a minor shift in the info record. They are vulnerable to their training skills, which makes them blunder in the collection of test data. The RF's various DTs are generated by combining different sections of the training dataset. To identify the substitution test, each DT of the forest must pass the information vector.

At this point, each DT reflects on the unique component of the input vector and gives a classification result. The forest then decides whether the Primary 'votes' (in consideration of a discrete classification result) or the form of all trees within the forest should be classified (for numeric classification result). Since the RF calculation affects multiple elective DTs, it can reduce the fluctuation that has arisen due to the thought of one DT for a comparable dataset.

5 Results and Discussions

The data set has been divided into two sections. The first data collection is classified as training data and the second is test data for assessment purposes. Test size was 0.3 i.e., the amount of data for the test split would be 30%. Accuracy calculates the predictions corresponding to the given X_Test, compares these predictions with Y_Test, which represents the real outcomes to the corresponding parameter. In the Higgs Boson dataset, the activities are divided into three interaction outcomes i.e., Mention (MT), Reply (RE), and Retweet (RT).

5.1 Performance Metrics for Classification Problem

Evaluation metrics examine data more accurately. So here we have analyzed data in terms of certain metrics such as precision, recall, F1 score, accuracy, confusion metrics, AUC-ROC, and log loss respectively.

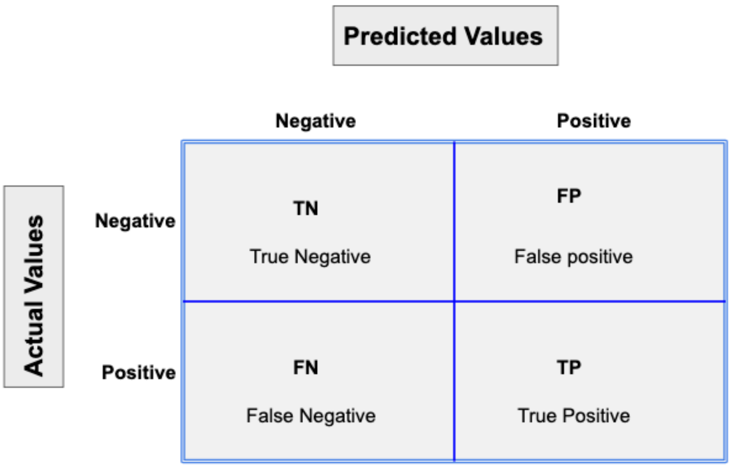

Figure 2: Confusion Metrics

5.1.1 Confusion Matrix

A confusion matrix defines the output of a collection of data put for the test for which truth values are known (i.e., the Actual Positives and Actual Negatives). Figure 2 shows, (1) True Positive (TP)-Rumor Predicted true + Actual true; (2) True Negative (TN)- Rumor Predicted false + Actual false; (3) False Positive (FP)- Rumor Predicted false + Actually false; (4) False Negative (FN)- Rumor Predicted false + Actual true.

5.1.2 Precision

It is the ratio of system results generated that correctly predicts positive (True Positive) observations to the overall forecast positive (True Positive) observations of the system (False Positives), explained as

$$\textbf{Precision} = \textbf{True Positive}(\textbf{TP}) \div (\textbf{True Positive}(\textbf{TP}) + \textbf{False Positive}(\textbf{FP}) \qquad (1).$$

Precision is high for day 1 spread of information in the Retweet (RT) in Table 3. It varies between 0.92 to 0.94 for K-Nearest Neighbor (KNN), Logistic Regression (LR), Decision Tree (DT), and Random Forest (RF). Similarly calculating precision with Reply (RE) network in Table 2 from 0.65 to 0.75 for all classifiers and 0.47 to 0.64 for Mention (MT) network in Table 1. We can observe that for the Retweet network (i.e., RT), there is an early indication of untrue/rumor content with high precision value.

5.1.3 Recall

It is the ratio of system results correctly predicting positive (True Positive) observations to all actual class (Actual Positive) observations. It can be explained from

$$\textbf{Recall} = \textbf{True Positive}(\textbf{TP}) \div (\textbf{True Positive}(\textbf{TP}) + \textbf{False Negtaive}(\textbf{FN})) \qquad (2).$$

As we can see in Retweet (RT) network in Table 3, has high recall value is observed to be 1 for 1 day at the beginning with Random Forest (RF) and Logistic Regression (LR) classifiers and highest achievable among the 3 classes. This signifies that the classifiers can distinguish rumor/ untrue information at an early stage in Mention (MT) and then in Reply (RE) and lastly on Retweet (RT) network respectively.

5.1.4 Support

Support can be described as the number of true response samples in each target class.

5.1.5 F1-Score

It is proportional to the relative contribution of precision and recall. Mathematically, the F1-score is the weighted average for precision and recall. The best value for F1-score would be 1 and the worst value would be 0. With the formula in equation 3, we can calculate the F1-score -

$$\textbf{F1} = \textbf{2} * (\textbf{precision} * \textbf{recall}) / (\textbf{precision} + \textbf{recall}) \qquad (3).$$

For ideal results, we need an ideal good classifier that calculates a harmonic mean of precision and recall values so we are using the F1 score to identify the class with early intervention of misinformation. F1 score predicts that Retweet Network works well for Logistic Regression (LR), Decision Tree (DT), K-Nearest Neighbor (KNN), and Random Forest (RF) classifiers in predicting untrue information for 24 hours from its origin. It shows a 0.98 value which is close to 1. Thus, it is observed that the F1 score is high as precision and recall are also high for the RT network.

5.1.6 Accuracy

It is simply the ratio of the correctly predicted classifications (both True Positives and True Negatives) to the total test dataset as

$$\boldsymbol{Accuracy} = (\boldsymbol{True\ Positive}(\boldsymbol{TP}) + \boldsymbol{True\ Negative}(\boldsymbol{TN})) \div (\boldsymbol{True\ Positive}(\boldsymbol{TP}) + \boldsymbol{FalsePositive}(\boldsymbol{FP}) + \boldsymbol{False\ negative}(\boldsymbol{FN}) + \boldsymbol{True\ Negative}(\boldsymbol{TN})) \qquad (4).$$

Accuracy works for the proportion of the total number of correct predictions. Here we can see that the highest achievable accuracy was found to 93.93% in Retweet (RT) network with LR and Rf classifiers for day 1 particularly. This predicts the trend of misinformation spread in the network from 1 day to 7 days.

5.1.7 AUC (Area under ROC Curve)

Area Under Curve (AUC) - Receiver Operating Curve (ROC) is a performance measure for classification problems based on various threshold values. AUC is a separation measure and ROC is a probability curve. This means that the AUC-ROC metric gives the model the capacity to distinguish classes. Better the model, higher the AUC. The threshold value of AUC ranges between 0.5<AUC<1, shows a high chance that the classifiers will be able to distinguish the positive class (i.e., untrue information) from the negative class (i.e., true information). So, the higher the value of AUC for the classifier, the better its ability to distinguish between positive and negative classes.

Table 1: Experimentation results of classifiers on Mention Tweets (MT).

Machine learning Algorithms	Evaluation Metrics (Unit (%))	Activities (Days)			
		1 Day	3 Days	5 Days	7 Days
K-Nearest Neighbor (KNN)	Precision	0.47	0.48	0.48	0.54
	Recall	0.43	0.44	0.47	0.23
	F1-Score	0.45	0.46	0.47	0.54
	Support	7345	7572	7882	9477
	Confusion Matrix	[[3155 4190] [3510 11668]]	[[3317 4255] [3561 11390]]	[[3666 4216] [3904 10737]]	[[5070 4407] [4325 8721]]
	Accuracy	65.81	65.29	63.94	61.20
	ROC Score	59.91	59.99	59.92	60.17
Logistic Regression (LR)	Precision	0.00	0.00	0.52	0.56
	Recall	0.00	0.00	0.00	0.28
	F1-Score	0.00	0.00	0.01	0.37
	Support	7345	7572	7882	9477
	Confusion Matrix	[[0 7345] [0 15178]]	[[0 7572] [0 14951]]	[[25 7857] [23 14618]]	[[2612 6865] [2081 10965]]
	Accuracy	67.38	66.38	65.01	60.28
	ROC Score	50.00	50.00	50.08	55.80
Decision Tree (DT)	Precision	0.57	0.60	0.60	0.64
	Recall	0.64	0.65	0.68	0.70
	F1-Score	0.60	0.62	0.64	0.67
	Support	7345	7572	7882	9477
	Confusion Matrix	[[4684 2661] [3538 11640]]	[[4929 2643] [3346 11605]]	[[5357 2525] [3562 11079]]	[[6637 2840] [3707 9339]]
	Accuracy	72.47	73.40	72.97	70.93
	ROC Score	70.23	71.35	71.81	70.80
Random Forest (RF)	Precision	0.00	0.00	0.52	0.56
	Recall	0.00	0.00	0.00	0.28
	F1-Score	0.00	0.00	0.01	0.37
	Support	7345	7572	7882	9477
	Confusion Matrix	[[0 7345] [0 15178]]	[[0 7572] [0 14951]]	[[25 7857] [23 14618]]	[[2612 6865] [2081 10965]]
	Accuracy	67.38	66.38	65.01	60.28
	ROC Score	50.00	50.00	50.08	55.80

Table 2: Experimentation results of classifiers on Reply Tweets (RT)

Machine learning Algorithms	Evaluation Metrics (Unit (%))	Activities (Days)			
		1 Day	3 Days	5 Days	7 Days
K-Nearest Neighbor (KNN)	Precision	0.75	0.73	0.73	0.67
	Recall	0.81	0.81	0.80	0.72
	F1-Score	0.78	0.77	0.76	0.69
	Support	16651	16260	16131	14640
	Confusion Matrix	[[13555 3096] [4507 1365]]	[[13104 3156] [4781 1482]]	[[12941 3190] [4864 1528]]	[[10572 4068] [5241 2642]]
	Accuracy	62.24	64.76	64.24	58.66
	ROC Score	52.32	52.12	52.06	52.86
Logistic Regression (LR)	Precision	0.74	0.72	0.72	0.65
	Recall	1	1	0.76	1
	F1-Score	0.85	0.84	0.83	0.79
	Support	16651	16260	16131	14640
	Confusion Matrix	[[16651 0] [5872 0]]	[[16260 0] [6263 0]]	[[16131 0] [6392 0]]	[[14640 0] [7883 0]]
	Accuracy	73.92	72.19	71.62	65.00
	ROC Score	50.00	50.00	50.00	50.00
Decision Tree (DT)	Precision	0.77	0.76	0.72	0.70
	Recall	0.77	0.77	1	0.72
	F1-Score	0.77	0.76	0.83	0.71
	Support	16651	16260	16131	14640
	Confusion Matrix	[[12812 3839] [3906 1966]]	[[12571 3689] [4049 2214]]	[[12232 3899] [4091 2301]]	[[10495 4145] [4577 3306]]
	Accuracy	65.61	65.64	64.52	61.27
	ROC Score	55.2	56.33	55.91	56.81
Random Forest (RF)	Precision	0.74	0.72	0.73	0.65
	Recall	1	1	0.80	1
	F1-Score	0.85	0.84	0.76	0.79
	Support	16651	16260	16131	14640
	Confusion Matrix	[[16651 0] [5872 0]]	[[16260 0] [6263 0]]	[[16131 0] [6392 0]]	[[14640 0] [7883 0]]
	Accuracy	73.92	72.19	64.24	65.00
	ROC Score	50	50	52.06	50

Table 3: Experimentation results of classifiers on Re-Tweets for 7 days.

Machine learning Algorithms	Evaluation Metrics (Unit (%))	Activities (Days)			
		1 Day	3 Days	5 Days	7 Days
K-Nearest Neighbor (KNN)	Precision	0.94	0.94	0.93	0.92
	Recall	0.98	0.98	0.97	0.98
	F1-Score	0.96	0.96	0.95	0.95
	Support	21156	21153	220974	20830
	Confusion Matrix	[[20808 348] [1354 13]]	[[20805 348] [1356 14]]	[[20448 526] [1529 20]]	[[20316 514] [1669 24]]
	Accuracy	92.44	92.43	90.87	90.30
	ROC Score	49.65	49.68	49.39	49.47
Logistic Regression (LR)	Precision	0.94	0.94	0.93	0.92
	Recall	1	1	1	1
	F1-Score	0.97	0.97	0.96	0.96
	Support	21156	21153	20974	20830
	Confusion Matrix	[[21156 0] [1367 0]]	[[21153 0] [1370 0]]	[[20974 0] [1549 0]]	[[20830 0] [1693 0]]
	Accuracy	93.93	93.91	93.12	92.48
	ROC Score	50.00	50.00	50.00	50.00
Decision Tree (DT)	Precision	0.94	0.94	0.93	0.92
	Recall	0.94	0.94	0.93	0.92
	F1-Score	0.94	0.94	0.93	0.92
	Support	21156	21153	20974	20830
	Confusion Matrix	[[19841 1315] [1354 13]]	[[19848 1305] [1357 13]]	[[19474 1500] [1533 16]]	[[19183 1647] [1677 16]]
	Accuracy	88.14	88.18	86.53	85.24
	ROC Score	47.36	47.38	46.94	46.51
Random Forest (RF)	Precision	0.94	0.94	0.93	0.92
	Recall	1.00	1.00	1.00	1.00
	F1-Score	0.97	0.97	0.96	0.96
	Support	21156	21153	20974	20830
	Confusion Matrix	[[21156 0] [1367 0]]	[[21153 0] [1370 0]]	[[20974 0] [1549 0]]	[[20830 0] [1693 0]]
	Accuracy	93.93	93.91	93.12	92.48
	ROC Score	50.00	50.00	50.00	50.00

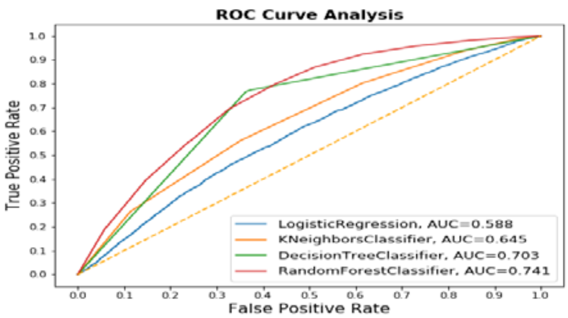

Figure 3: ROC(AUC) Line Curve for 1 day(RT)

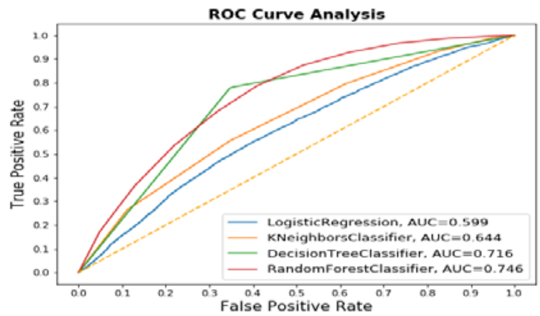

Figure 4: ROC (AUC) Line Curve for 3 days (RT)

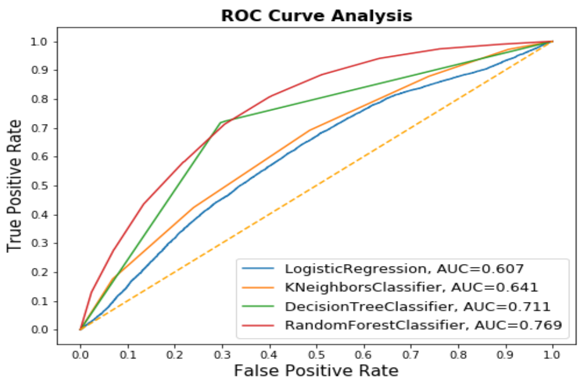

Figure 5: ROC (AUC) Line Curve for 5 days (RT)

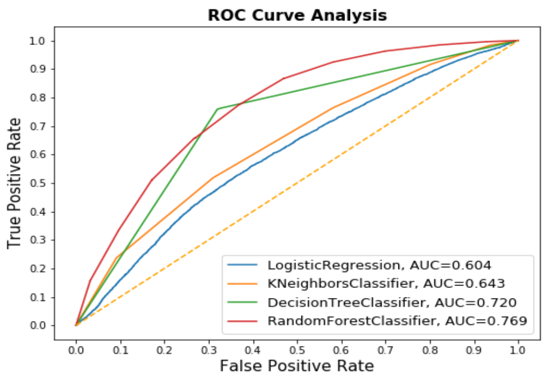

Figure 6: ROC (AUC) Line Curve for 7 days (RT)

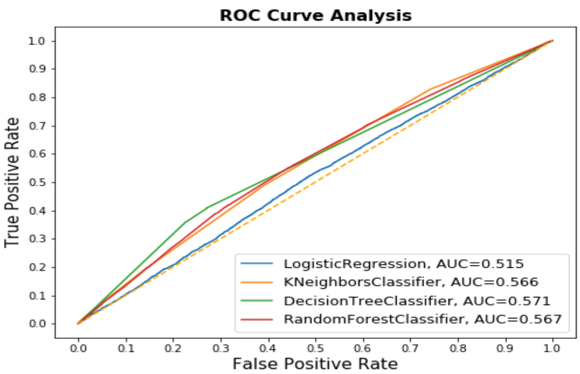

Figure 7: ROC (AUC) Line Curve for 1 day (RE).

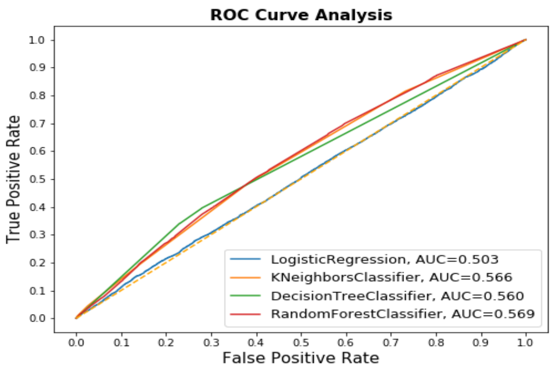

Figure 8: ROC (AUC) Line Curve for 3 days (RE).

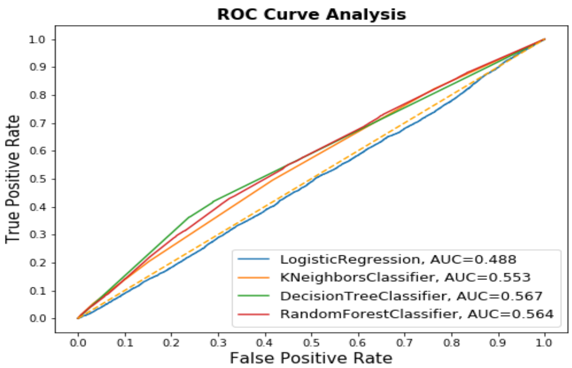

Figure 9: ROC (AUC) Line Curve for 5 days (RE)

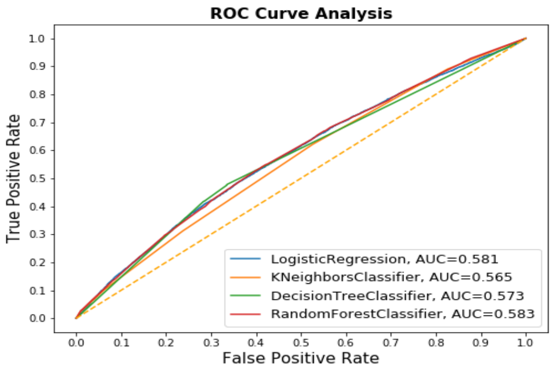

Figure 10: ROC (AUC) Line Curve for 7 days (RE)

ROC curve is a plot between sensitivity is True positive rate (TPR) and (1-sensitivity) known as False positive rate (FPR). Figures 3-14, confirms that the Retweet network (RT) varies in the range of AUC-ROC threshold is 58% with Logistic Regression (LR) to 74% with Random forest (RF) for day 1. Similarly, threshold value of 50% to 56% in Retweet (RT) network. Mention (MT) suffers from the misclassification of data as the threshold values range between 40% to 50% for 1day to7 days respectively. Thus, AUC-ROC in the order gradually gives Random forest being the best-suited classifier for early detection of untrue information in the network.

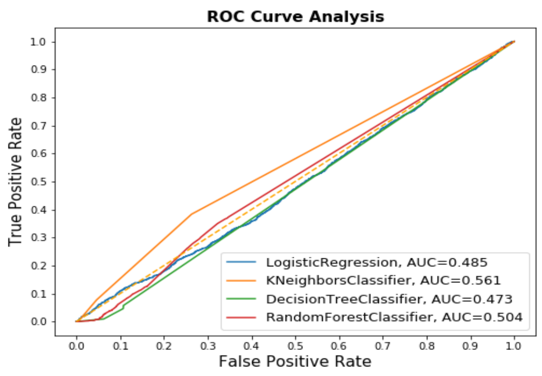

Figure 11: ROC (AUC) Line Curve for 1 day (MT)

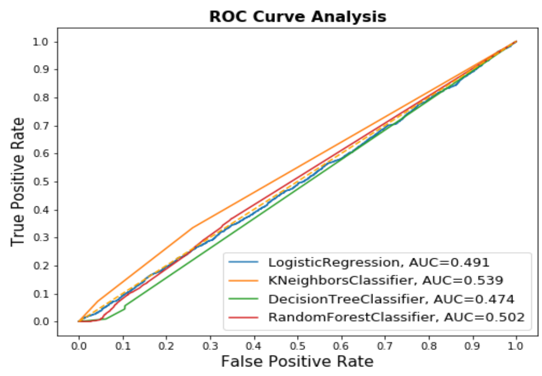

Figure 12: ROC (AUC) Line Curve for 3 days (MT)

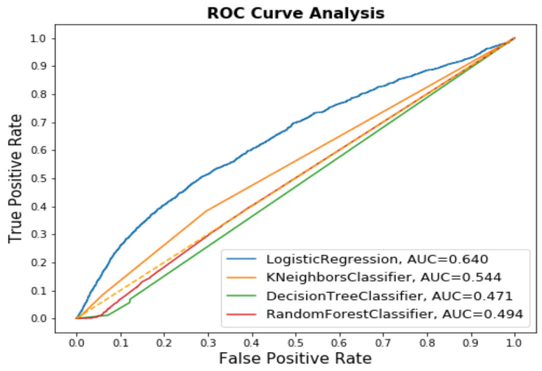

Figure 13: ROC (AUC) Line Curve for 5 days (MT).

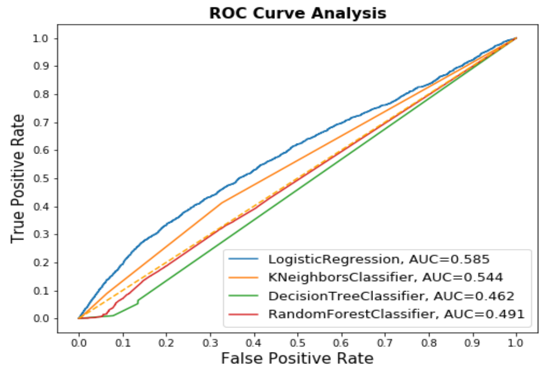

Figure 14: ROC (AUC) Line Curve for 7 days (MT).

6 Conclusion

Substantial studies have been conducted to determine the source of the rumors and to detect the rumors. The paper uses classification measures to determine its distribution across the network. This paper presents an early rumor detection technique and conducts a comparative study of machine learning approaches. The results confirm that the dynamic modeled data with supervised classification problems give early detection of scientific rumor/untrue information content. By examining and calculating evaluation metrics provides a clear indication of early identification of untrue information in Retweet (RT) class with an accuracy measure of 93.93% with Random forest (RF) classifier with AUC-ROC threshold 74% with day 1 itself. Thus, RF worked well as compared with KNN, DT, and LR. Our approach is efficient and effective in predict untrue information, possibly appearing early (i.e., for 1 day) in MT, RE, and RT.

7 Availability of Data and Material

Information can be made available by contacting the corresponding author.

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